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Stochastic optimization in tactical supply chain risk management

Bachelor's thesis

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Työssä käsitellään yritysten toimitusketjujen hallintaa, toimitusketjujen riskienhallintaa ja näiden suunnitteluun sekä hallitsemiseen käytettävää stokastista optimointimallia. Malli implementoidaan Microsoft Excelin avulla. Työn tavoitteena on validoida työssä käytetty stokastinen optimointimalli. . Lisäksi työssä vertaillaan mallin antamia tuloksia erilaisille tavoitetiloille: toisessa tilanteessa päätöksentekijä pyrkii minimoimaan riskit ja toisessa maksimoimaan voitot. Mallille tehdään myös herkkyysanalyysiä. Työn rakenne on seuraava: johdannossa esitellään työn asiakokonaisuuksia yleisesti, kappaleessa kaksi tarkastellaan aiheeseen liittyvää kirjallisuutta, kolmannessa kappaleessa esitellään käytettävä optimointimalli, neljännessä kappaleessa käsitellään esimerkkejä implementoinnista ja mallin tuloksia ja viimeisessä kappaleessa kootaan työn havainnot yhteen.

Toimitusketjujen hallintaan kuuluu paljon muuttuvia tekijöitä, joita on hankala ennustaa tarkasti. Yritykset tarvitsevat erilaisia malleja toimitusketjujen suunnitelmalliseen hallintaan päätöksenteon tueksi. Suuryritysten johdot ovat nykypäivänä ymmärtäneet riskienhallinan merkityksen pelkän maksimaalisen voiton tavoittelemisen sijasta: yritysten toiminnan tulee olla kannattavaa pitkällä aikavälillä, minkä takia riskienhallinta on olennaisessa roolissa yritysten toiminnan suunnittelussa.

Yritykset koostuvat useista toiminnallisista yksiköistä. Jokaisella yksiköllä on omat tavoitteet ja resurssit, joiden puitteissa he pyrkivät maksimoimaan omaa kannattavuuttaan. Myynnin ja operaatioiden suunnitteluprosessin (S&OP) avulla pyritään maksimoimaan koko yrityksen kannattavuutta huomioiden mahdolliset riskitekijät sekä reunaehdot eri yksiköiden osalta.

Stokastisessa mallinnuksessa alku- sekä lopputila riippuvat toisistaan siten, että niiden välillä tapahtuu jotain tiettyä jakaumaa noudattava satunnainen tapahtuma. Stokastisessa optimoinnissa huomioidaan koko systeemin optimaalisuus siten, että kokonaisuus huomioidaan yksittäisen tilan muuttumisen yhteydessä. Stokastiset optimointimallit soveltuvat erityisen hyvin toimitusketjujen ennustamiseen ja niiden riskienhallintaan.

Työssä käsitellään mallia, jonka on esitellyt Sodhi (2011). Sodhin mallin ideana on minimoida riskiä stokastisen optimoinnin menetelmien avulla. Käytännössä mallin tavoitteena on tehdä tulojakaumasta tasaisempi. Tämä tarkoittaa käytännössä sitä, että mikäli päädytään epätoivottuun tilaan, niin suuria tappioita ei silti aiheutuisi.

Mallia tutkittiin kahdesta eri näkökulmasta: riskin minimoinnin ja tuottojen maksimoinnin kannalta. Riskiä minimoimalla päädytään varmemmin tekemään tuottoja, mutta odotettu tuotto on suurempi tuottoja maksimoimalla. Työssä havaitaan myös se, että malli sopisi parhaiten arvioimaan tuotantokapasiteettia funktionaalisille tuotteille, joiden kysyntä on pitkällä aikavälillä tasaista. Erityisenä hyötynä pidettiin sitä, että mallin implementointi on suoraviivaista. Lisätutkimusta aiheesta voisi tehdä esimerkiksi implementoimalla malliin mahdollisuuden lisäinformaation huomioimisesta kuluvan kauden aikana.

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Avainsanat: stokastinen optimointi, toimitusketjun riskienhallinta, riskienhallinta, optimointimallin implementointi Excelissä, myynnin ja operaatioiden suunnittelu

AALTO UNIVERSITY SCHOOL OF SCIENCE PL 11000, 00076 AALTO http://www.aalto.fi	SUMMARY OF BACHELOR'S THESIS

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In this Thesis a stochastic optimization model is presented. The purpose of the model is to calculate optimal supply requirement for each time period. A literature review is conducted on supply chain management, supply chain risk management and stochastic optimization. The model will be implemented with Microsoft Excel. The goal of this Thesis is to validate the stochastic optimization model presented by Sodhi (2011). Additionally the results of two different optimization scenarios are discussed: in another scenario the decision maker attempts to minimize the risks and in the other one the purpose is to maximize the profits. A sensitivity analysis will be conducted also. The structure of the Thesis is as follows. In Chapter 2, relevant literature is reviewed. In Chapter 3 the model and its implementation in Excel is described in detail. In Chapter 4 the results of the model are discussed and Chapter 5 concludes.

Supply chain management involves many changing factors, which are hard to predict precisely. Managers need tools, for example mathematical models, to manage companies in a holistic and predictable manner. Nowadays the managements of corporations have realized the importance of risk management instead of simply attempting to achieve maximal profits. The activities of a company must be profitable in the long run, which is why risk management is playing essential role in planning company's actions.

Companies consist of numerous smaller operational units. Every unit has their own goals and resources with which they are attempting to optimize own profitability. Sales- and operations planning -process (S&OP) is a process with which it is attempted to consider all essential parts of the company in order to find a global optimal way of managing it.

In stochastic modeling a random event will happen between the start and end stage. The probability distribution of the random event is known or can be estimated. In stochastic optimization the optimality of the whole system is taken into account. Stochastic optimization models are especially good for modeling changes in supply chain system and for supply chain risk management.

In this Thesis the stochastic optimization model which will be discussed was initially published by Sodhi (2011). The basic idea of the model is to minimize risk using stochastic optimization methods. In principle, the goal of the model is to make the distribution of profits more flat in such manner that the highest profits are lower than they would be while maximizing profits, but the losses in the tail probabilities are also lower. This way the worst-case –scenarios will not be as disastrous as they could be. The model was examined from two points of view. Another one was to minimize risks and the other was to maximize profits. By minimizing risk the probability of making profits was higher contrary to profit maximization. On the other hand, the expected profits were higher with profit maximization compared to risk minimization.

As a results it was found that Sodhi's model would suit best to model the supply requirement for functional products, whose demand is stable in the long run. The best attribute of the model is that it can be implemented using regular office tools, such as Microsoft Excel. The implementation is also relatively simple. Further research could be done in implementing an option to the model to take more demand information into account during the life cycle of the product.

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Contents

Symbols and abbreviations

λ_1 = Weight of cIaR
λ_2 = Weight of cBaR
λ_3 = Weight of cDaR
$cIaR$ = Conditional Inventory-at-Risk
$cBaR$ = Conditional Borrowing-at-Risk
$cDaR$ = Conditional Demand-at-Risk
T = Planning horizon
t = Period number
s = State number
u = Percentage amount of increase in demand per period
d = Percentage amount of decrease in demand per period
$m_{\sigma_t^s}$ = Material balance at period t at state s
$g_{\sigma_t^s}$ = Inventory level of product at period t at state s
$u_{\sigma_t^s}$ = Unmet demand of product at period t at state s
$z_{\sigma_t^s}$ = Sales of product at period t at state s
$I_{\sigma_t^s}$ = Amount of cash in account during period t at state s
$y_t =$ Supply requirement at period t
D_t^S = Demand at period t for state s
$\alpha =$ Tail probability
$\pi =$ Realized price from selling one product
k_{prod} = Marginal cost of producing one unit
k_{inv} = Cost of carrying inventory
k_{back} = Penalty for each product that is not delivered
$b_{\sigma_T^s}$ = Borrowing at final period T in state s
T = Planning horizon in weeks
SCM = Supply chain management
SCRM = Supply chain risk management
VaR = Value-at-Risk
CVaR = Conditional-Value-at-Risk

1 Introduction

Managers have become more aware of the importance of enterprise risk management. In decision making, the desired outcome includes risks which must be taken into account in the decision process. Typically when making such decisions in uncertain environment, estimation or forecasting of uncertainties is essential; for example when adjusting production capacity, a sales or demand forecast is particularly useful.

Risk management is important in supply chain management (SCM). Successful SCM depends on many factors which cannot be forecasted precisely. This is why companies need model-based tools to manage supply chains. These tools should also consider the operations of the company in a holistic manner instead of treating each operation separately, which leads to sub-optimization.

In this Thesis we focus on supply chain risk management (SCRM) in general and specifically evaluate how a particular stochastic optimization model can be used to support decision making in SCRM. We also illustrate what the model implies to sales-and-operations-planning -process (S&OP) with numerical examples. This is done by introducing an Excel implementation of the model presented by Sodhi (2011). Along with the results, we also discuss of further development ideas related to the model.

The main objectives of this Thesis are to cover the basic concepts of SCM and SCRM, validate the model, conduct sensitivity analysis for the model and to compare risk minimized results with profit maximized results.

The structure of the Thesis is as follows. In Chapter 2, relevant literature is reviewed. In Chapter 3 the model and its implementation in Excel is described in detail. In Chapter 4 the results of the model are discussed and Chapter 5 concludes.

2 Literature review

2.1 Supply chain management

According to Christopher (1998) *a supply chain is a network of organizations that are involved, through upstream and downstream linkages in the different processes and activities that produce value in the form of products and services in the hand of the ultimate consumer*. There can be numerous different parties involved in the process of managing a supply chain. This makes managing the chain a complex task, and also aggravates risks caused by uncertainties in different parts of the chain. SCM is about coordinating materials, information and financial flows in order to fulfill customer demands while keeping the business competitive (Stadtler 2005). Efficient supply chain management is essential for companies because it is such an integral part of the companies` whole operations and supply chains can define how competitive a company can be. One way of

gaining more competitiveness is to outsource all non-core-operations and focus only on the core-competences which is why firms often outsource their supply chain operations (Tang 2006).
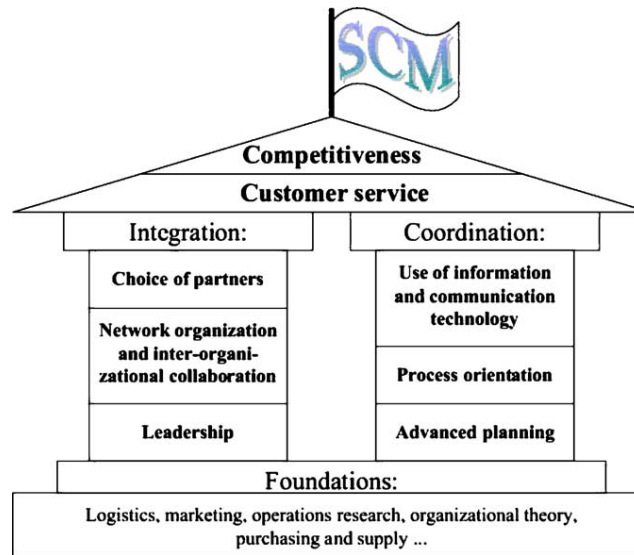
Figure 1 House of SCM (Stadtler 2002)

Stadtler (2005) describes SCM as a house of blocks (Figure 1), which define the most integral parts of SCM. The roof of the house, which consists of competitiveness and customer services, is supported by two pillars: integration and coordination. In the end, competitiveness and customer service is about how well the operations of different blocks in the pillars are managed.

The first pillar, coordination, consists of the following subjects: use of information and communication technology, process orientation, and advanced planning. The model presented in this Thesis provides an example how sales forecasts can be adjusted for risk management purposes. Also the process orientation of the company is not only about making company's behavior more predictable by processes; it is also about integration between different partners.

The pillar integration consists of three different sections: choice of partners, network organization and inter-organizational collaboration and leadership. Nowadays with internet the information exchange between parties involved in a supply chain has become faster and it has opened new opportunities for forecasting demand. While increased opportunities to forecast have led to operational efficiency, it also causes Bullwhip effect, which is a known problem in SCM (Lee et al. 1997). One cause for the Bullwhip effect is that the upstream suppliers do not have as accurate market data as the first hand stores, which us is why their forecasts tend to react more radically to changes in demand. This effect can be diminished using sales forecasts and open information exchange. The model we study produce risk-adjusted sales forecast, which can be used in planning the upcoming periods. Also in cases when demand is uncertain, the model can be used to provide multiple scenarios of possible outcomes in order to prepare your suppliers for the next season.

The last building block of SCM is advanced planning. Advanced planning is about making the plan how a procurement, production, distribution and sales of the product. It involves three kinds of plans: plan for long-, mid- and short-term. Strategic network planning is a long-term plan, for

example, of how the warehouses, the production sites, capacities and transportation are organized. The mid-term plan for adjusting the supply chain to fulfill demand forecasts and makes sure there are not any bottlenecks. This process is often referred as sales and operations planning (S&OP) process, which is the key process related to this Thesis. Short-term plan takes care of how and where to buy the materials, requirements planning, production planning, scheduling, distribution planning, transport planning, demand planning and demand fulfillment (Meyr et al. 2002).

2.2 Product characteristics

Basically there are two different kinds of products: functional and innovative products (Lee 2002). Functional products have more stable demand because of longer life cycles. Another type is innovative products. The demand of innovative products is usually uncertain and the life cycles of such products are shorter. Such as high-technology products are usually considered as innovative products, and examples of functional products include such as food and oil.

Another way of dividing products is the way how it is manufactured: is the process used to manufacture the product an evolving or a stable process (Lee 2002). A stable process has reached a "mature" state which means the underlying technology is established, while the technology for evolving process is still under early development and is rapidly changing. Evolving process is also riskier than a stable process.

Especially for new products it is extremely hard to forecast demand because there is no historical data and it is difficult to know about the customer preferences. In general it is also important to get your forecasts right because almost always the inappropriate supply plan will result in major losses. These problems can be alleviated by conducting a marketing research to get information about potential customers and by using forecasting models as the one in this Thesis to optimize the supply plan.

2.3 Supply chain risk management

According to Tang (2006) supply chain risk management (SCRM) is defined as the management of supply chain risks partners so as to ensure profitability and continuity. Supply chain risk management can be divided into two dimensions (Tang 2006):

1. Supply chain risks – operational risks or disruption risks
2. Mitigation approach – supply management, demand management, product management or information management

Operational risks include uncertain customer demand, uncertain supply and uncertain cost. Disruption risks are referred as major disruptions caused by natural or man-made disasters such as hurricanes, terrorist attacks, floods or earthquakes.

In the following chapters we will introduce means to reduce demand or supply uncertainty. Practically this means the reduction of risks involved in the supply chain.

2.3.1   Supply management

Supply management is about a firm coordinating or collaborating with upstream partners to ensure efficient supply of materials along the supply chain. Basically supply management can be divided into five different topics: supply network design, supplier relations, supplier selection process, supplier order allocation and supply contracts (Tang 2006).

Supply network design considers five main points in planning the network: network design, product assignment, customer assignment, production planning and transportation planning. By using global suppliers companies can gain many advantages compared to just having partners from one certain region. For instance firms have a better chance of surviving major disasters because they have an option to choose from different partners. This gives also a possibility for a firm to use most economical choices for their suppliers: they can consider which currency is most suitable for them, which government gives them the best subsidies and tax incentives. Huchzermeier (1996) shows how companies can take advantage of the fluctuations of exchange rates and also how a firm can hedge their supply chain against currency uncertainties using real options.

As mentioned before, firms have realized that by outsourcing the supply operations they can focus more in their core-competences. In practice this means reduced costs, reduced product development cycle time and increased product quality. It is not always optimal to use long-term contracts and in some conditions short-term contracts are the optimal ones (Cohen et al. 1999). According to Tang (1999) there are four different types of relationships: vendor, preferred supplier, exclusive supplier and partner. Main differences between these are the types of contracts, length of contracts, type of information exchange, pricing scheme and delivery schedule.

One way to diminish risks involved in a supply chain is to choose and negotiate good contracts with different partners. Contracts give firms guarantees so that their actions become more predictable and systematic. On the other hand the management (and optimization) of a supply chain should be done as a whole, because the independent decisions can cause operational inefficiency and suboptimal decisions for the whole supply chain (Tang 2006).

2.3.2   Demand management

Demand management includes coordinating or collaborating with downstream partners to influence demand in a beneficial manner. Usually supply of products can be estimated in good detail but demand is not easy to estimate. That is why firms have developed different ways to manipulate demand. According to Tang (2006) the most important ways to control demand are price postponement strategy, shifting demand across time, shifting demand across markets and shifting demand across products. Demand and the efficient use of materials can also be handled by product differentiation.

Price postponement strategy has same features as "order first and based on the initial sales data update your sales forecast and do another order if necessary". In this strategy after the first order and initial sales data, the demand can be controlled by changing the price to make the supply meet demand more accurately. The same kind of strategy with pricing can be used to change demand in

high-seasons and offering discounts during low-seasons. This also helps the firms to catch different segments of customers: not everybody is willing to pay the highest price even in the high season, but there are always people who are willing to do so. By offering discounts for people who do their orders in advance firms are able to plan their actions more carefully.

Global firms can take advantage of shifting demand across markets. A very good example of this is about seasonal products: the selling of ski wear in the USA usually ends in May and the same season for South America usually begins in June[7] so firms can get significant competitive advantage by selling their products in both markets (Tang 2006). First of all, they get sales data from USA before going to South American markets. Second, the first order of products (products meant for USA) includes significantly less risk than selling products in one market because the stock that was not sold can be sold in the other market.

By having complementary and substituting products firms can manipulate the demand. Tang (2006) presents two different kinds of approaches for this: product substitution and product bundling. Firms can do product substitution in many ways. First of all, they need products that have same features and abilities which enable them to shift demand from another product to another. Secondly, they can use pricing mechanisms to drive people to buy the substituting product because of surplus stock. This can be done by for example with discounts. Second approach for demand manipulation with products is product bundling which basically means that firms sell products in packs. For example by buying a computer you might get a printer with it or with a shampoo you get a conditioner. This forces the customers to buy both of these products which can be an efficient way of getting rid of surplus inventory.

2.3.3 Product management

With product management, a firm can gain advantages by modifying product portfolio or the design of processes that will make it easier to make supply to meet demand. According to Tang (2006), product variety is an effective strategy for the firm to increase market share. One way to overcome the problem with complex manufacturing processes is to produce different products which have the same basic platform. Such an approach is widely used in the computer industry for example.

In the context of product management, we shall present two different management strategies: postponement and process sequencing (Tang 2006). Postponement is about postponing the state when to differentiate a certain product: basically this means that the state is "when the platform is ready" for the product. According to Lee et al. (1997), product differentiation can be achieved via standardization of components and subassemblies, modular design, postponement of operations and re-sequencing of operations. One major result of postponement is the reduction of inventory levels. It also gives companies more time to see how the demand will develop and do the required differentiation based on the orders.

Another way to reduce risks is to find a new sequence for manufacturing processes. For example in woolen garment industry everything is done in dye-first-knit-later sequence because it gives firms more freedom in designing their products. On the other hand for some woolen products it might be

more efficient to use knit-first-dye-later approach in cases where there are only simple colored products (Tang 2006).

Sport Obermeyer uses a way to reduce inventory uncertainty by rethinking and re-planning their products and supply chain (Fisher et al. 1994). Sport Obermeyer provides for example fashion skiwear. Before they tried to use different colored zippers to match the color of the cloth but then they rethought the product and the process of making it. In the result of this they found that by using mostly one kind of zippers they can reduce lead times significantly: sometimes the absence of certain zipper can cause delay of months for a single fashion product.

2.3.4   Information management

Different information management strategies are needed for different kinds of products. According to Fisher et al. (1994) in 1992 based on initial forecasts General Motors allocated half of one of their plants production for redesigned Seville and Eldorado models. However, the demands for models exceeded the supply and therefore GM tried to alter their production plan. They devoted 86% of this plant's production for producing only these demanded models. Eventually they devoted the whole plant for it, but meanwhile they were doing the modifications they lost thousands of customers: the damage had been done already.

GM's example offers a telling example of the importance of getting forecasts as precise as possible. One way to improve the forecasts is to update the forecasts as firm gets more sales information. This would need the retailer to place multiple orders per season, which may cost more but by multiple orders retailers are able to reduce their losses. It is argued that by updating forecasts with initial sales data a company can improve its profits (Tang 2006). On the other hand, forecast update is only one indicator and companies should seek for other alternative indicators for coming sales. Sport Obermeyer found that they can improve their forecasts by gathering a panel of experts to make independent forecasts of each product. After analyzing everybody's forecasts variance they are able to find a unifying trend in each of the forecasts and therefore they are able to find what might be the real demand of the product (Fisher et al. 1994).

Especially for products which have long life cycles the suppliers are farther away from customer data which makes such supply chains more exposed to the bullwhip effect (Tang 2006). It is presented by Lee et al. (1997)[19] that the root causes for bullwhip effect are: demand forecasting, batch ordering, supply shortage and price variations. They offer that the bullwhip effect can be mitigated by using information sharing, vendor managed inventory and collaborative forecasting and replenishment planning.

Many companies have reported that sharing information between partners in a supply chain is beneficial for everybody but there are obstacles in sharing private information such as inventory level, demand forecasts or customer demand (Tang 2006). Retailers might be reluctant to share information with the manufacturer because of fear of losing competitive advantage: they could get lower bargaining power, information leakages etc. (Tang 2006). In some cases it is shown that sharing forecasts can end up in a lose-lose situation with retailer and manufacturer. More detailed explanation is offered by Terwiesch et al. (2005).

Vendor managed inventory (VMI) is an arrangement between a retailer and a manufacturer. Retailer provides certain information to manufacturer and the manufacturer takes full responsibility for maintaining an agreed inventory level for retailer (*"Vendor Managed Inventory"*). This gives guaranteed service levels for the retailer and reduces overall operating costs associated with replenishment planning (Tang 2006). Manufacturers gain several advantages also. First of all, they have direct access to customer demand data which can be used to reduce the bullwhip effect and therefore make the forecasts and production more accurate. Secondly, they can reduce operations costs due to coordinated production/replenishment plans for all retailers.

In VMI not that much collaboration is done on the field of forecasting. Voluntary Inter-industry Commerce Standards (VICS) provides an initiative called Collaboration Planning, Forecasting and Replenishment (CPFR) (Tang 2006). Under this initiative retailer and manufacturer share information about demand forecasting and they form a demand forecast together which they both agree on. The model presented in this Thesis could be a valuable tool in this process.

2.4   Sales and operations planning process and risk management

Companies consist of different functioning units, such as marketing, production and finance. Each one of these has their own goals and resources and therefore they try to maximize their own profitability. Sales and operations planning (S&OP) is a process to control these different sections as a whole. S&OP is about maximizing the profitability of a whole system, not just the results of individual units.

The author's experience from the industry exemplify the problems of bad coordination between sales and operations: in one company, the over-selling by a sales unit caused production capacity constraints, which eventually had a tremendous effect on customer satisfaction. This is a common problem in rapidly growing firms. But it is not necessarily about incompetent management because it can be the strategy of the whole company. For example it might be profitable to make delivery contracts even when knowing that the products will not be delivered on time because of overloaded production. In such situations the management considers the sanctions of the delays and might take that into account while pricing the product.

Sales forecast can be very inaccurate. Companies must make decisions on which factors they consider important and based on these to do the production adjustments. Here, sales forecasting has an essential role: even a guess is better than anything at all. One can also choose the decision parameters for the approximation in such way that the result can bear some risk: the expected value is just an average of what will happen, it will not happen every time, or maybe never. That is why the expected value should not necessarily be a leading factor in the decision making process: different supply scenarios should be thought as a whole. More specifically, the supply/demand scenarios can be thought as distributions and to minimize the overall risk, one can also minimize, e.g, worst-case costs in the tail of resulting cost distribution, instead of expected cost.

2.5 Stochastic programming and probability distributions

Stochastic optimization is suitable for supply chain systems because in stochastic models the uncertain nature of these systems can be taken into account (Birge et al. 1997). One feature of stochastic programming models is that it involves dynamic decision making between stages. This allows taking into account the random events occurring between the stages. Also the decisions are made in such way that it considers what is best for the whole time span and not just for the next step. The main application areas of stochastic programming are in supply chains, financial sector, energy power systems and transportations industry (Morton 2004). In stochastic programming, the uncertain nature of events can be taken into account and it is assumed that the probability distributions of certain events are known or can be estimated.

Stochastic programming can be divided into two categories, two-stage and multi-stage problems. In two stage problems there is only the initial situation and the second stage. A random event occurs between the two. In the second stage a recourse action is taken to adapt to the event which occurred. Figure 2 describes this process.
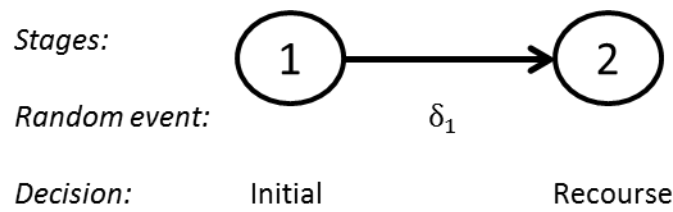

Figure 2 Two-stage stochastic problem (Dormer et al.)

Multi-stage stochastic programming is like two-stage problem but multi-stage includes multiple stages in the whole process. Between the stages occurs random events and the decisions are done dynamically between every stage. Dynamically means in this concept that the decisions consider the random events which occur between the decisions. The model discussed in this Thesis essentially solves a multi-stage problem Figure 3 clarifies the difference.
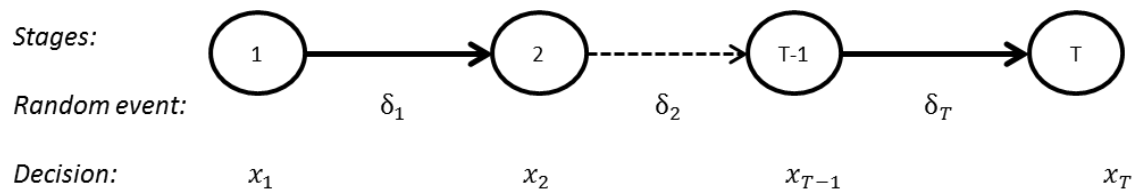

*Figure 3 Multi-stage stochastic problem (Dormer et al.)[3]*

If there are conditional probabilities between the stages then the problem is path dependent. This means that the current state does not describe the system fully, but also the path to this state matters. Different scenarios include the history of the events and in state specific model only the status of the current state matters in principle. Therefore, in one optimization problem with binary branching of scenarios, there is $2^{T+1} - 1$ different scenarios, where T is the number of time periods. Basically the number of scenarios will grow exponentially and therefore it is not practical (or it may

be impossible) to find an optimal solution. Usually in such cases scenario aggregation is used. In short, aggregation is about calculating the value of the next state based on the previous "upper" and "lower" state values. This way the scenario specific values can be converted into state specific values. Aggregation is not in scope of this article and we refer to Sodhi (2011) for more details.

In stochastic programming, it is possible to use different decision variables and approaches to the underlying problem. Usually the main objective is to maximize profit, which can imply high risk levels as we illustrate later. Therefore it might be practical to think different approaches to such problems. For example one might want to minimize risk instead of maximizing profit. From a practical point of view, it can be more sustainable in the long run to minimize risks because usually the excessive profits include great risks, and by minimizing risk the company's actions are more predictable and stable.

Also different decision variables may be used. The usual approach is to minimize the use of resources. One another approach is to minimize the probabilities of unwanted scenarios. One approach would be to minimize the losses if things happened in a very unpleasant way because usually the extreme events are the most harmful. Usually the outcomes around the expected value are the ones we mostly wish to happen. Therefore it might be vise to minimize the losses which might occur in the tails of the probability distributions.

Value-At-Risk (VaR) is a commonly used risk measure of risk of loss on a specific portfolio of a financial asset, but it can be applied for other similar cases also ("Value-at-Risk"). VaR is the value (loss) that will occur with some specified probability. The risk level can be adjusted by changing the length of the tail in probability distribution i.e. by changing the probability to match the desired maximum amount of losses the decision maker is willing to bear. Figure 4 presents a 10% VaR of a price (75€) whose average is 100€ (original picture from Bojoly (2010)). The colored area in Figure 4 represents prices for the product which will occur with less than 10% of probability.
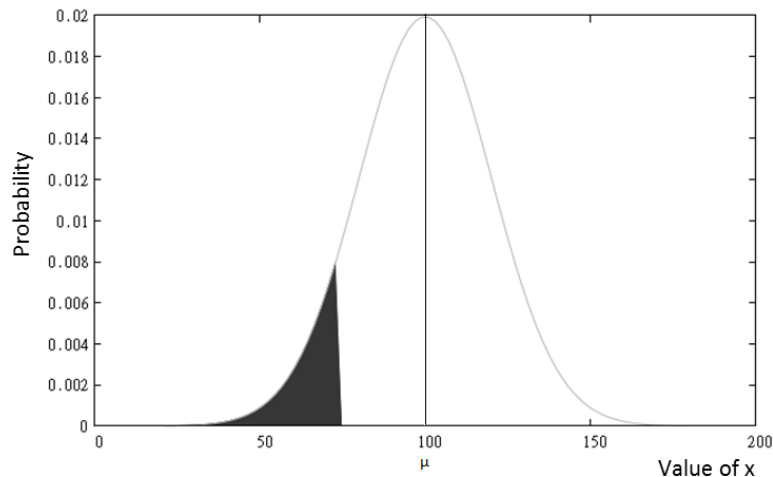
Figure 4 Value-At-Risk

Conditional-Value-at-Risk (CVaR) is also commonly used in risk measurement. CVaR is the expected value of the losses exceeding the value at risk, as illustrated in Figure 5. Therefore, it is a good

measure for minimizing the losses at tail probabilities. CVaR can also be adjusted to match the decision maker`s preferences by changing the probability in the same way as with VaR.
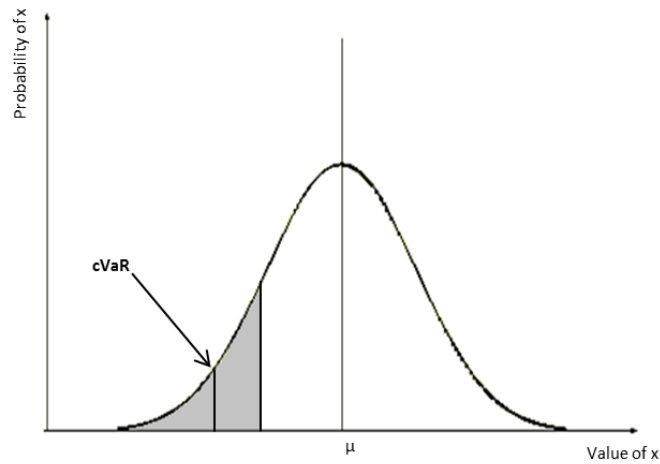

Figure 5 Conditional Value-At-Risk, µ is the expected value of x, cVaR is the weighted average of the losses exceeding the value at risk.

3 Stochastic optimization model for Sales & Operations Planning process

3.1 Basics of the model

The model we discuss in this Thesis provides a solution for the following problem. The decision maker knows the production cost of one product, the cost of carrying inventory of one product, the cost of unmet demand for one product, selling price of one product, the planning horizon and the demand scenarios for different time periods. The model can be used to define optimal supply requirement for different time periods. A decision maker can determine supply requirement for memory chips over a period of time for example. In principle Sodhi's model is about minimizing risk, not maximizing profit. Specifically, the model minimizes the losses in case demand ends up in a state which is an unlikely outcome, or distribution tail.

The objective function is a weighted sum of three risk measures: conditional borrowing at risk (cBaR), conditional inventory at risk (cIaR) and conditional demand at risk (cDaR). The sum of these is minimized. The decision variable is the required supply quantity per period. To solve the problem, we need to define marginal cost per unit (k_{prod}), price per unit (π), cost of carrying inventory (k_{inv}) and penalty of backordering (k_{back}). Also to calculate the conditional values we must decide which tail-probability to use in order to define the preferred risk level as described in section 2.5. In our case, we consider risk levels between 5% and 10%; due to discrete scenario allowance, this level varies depending on whether one or both tails are considered.
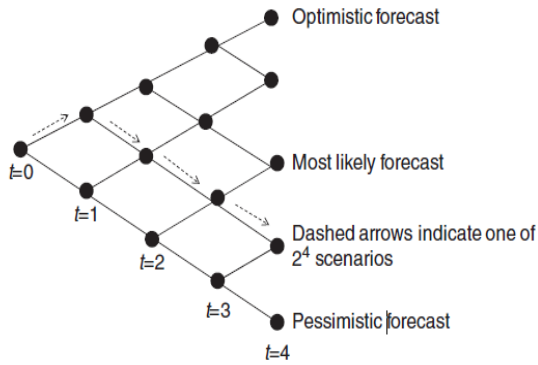
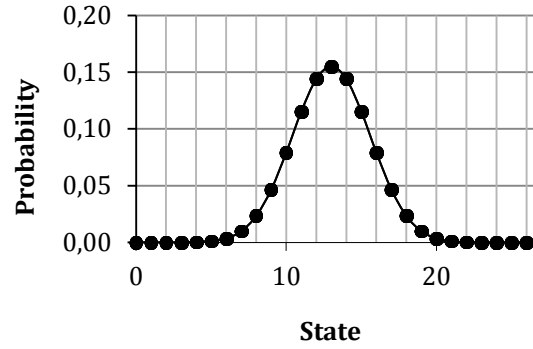Figure 6 Different demand scenarios (Sodhi 2011)

Figure 7 Probabilities of different states at t = 26

Demand uncertainty is represented as binominal lattice. Such lattice is generated by calculating the extreme values and the 'most likely one' as illustrated in Figure 6. The most optimistic and pessimistic demand is calculated by expecting a certain percentage growth/decrease in each node. The most likely one is in the middle, which is expected to be the same as in the beginning. Then the values between the most likely and the pessimistic/optimistic are approximated using linear interpolation. In this model it is assumed that it is fifty-fifty chance to go either up or down between the nodes. This implies that the probability of each node can be calculated by using a binomial distribution (see Figure 7).

The main problem in scenario based models such as this is that there are $2^{T+1} - 1$ different demand scenarios (paths), where T is the amount of time periods. For example for T = 26 (which may be appropriate planning period for electronic devices) there are more than 134 million demand scenarios which is not practical for optimization. This problem is solved by aggregation: the scenario specific values are transformed to state specific values, so we can handle the values as individual states. This way we must not take the path into account and the problem is much easier to solve because the size of the problem is reduced to $\frac{T(T+1)}{2}$ different states. This implies that in our case, there are 378 states and 27 end states. Different state values are constructed by taking an average of two preceding state values. Basically this means that value of next state is the average of preceding state values. More detailed discussion of aggregation is presented by Sodhi (2011).

3.2   Model implementation in Excel

The model formulation is:

$$min \quad \lambda_{cBaR} \cdot cBaR + \lambda_{cIaR} \cdot cIaR + \lambda_{cDaR} \cdot cDaR \ (1)$$

$$s.t. \qquad y_t - D_t^s = m_{\sigma_t^s} \ (2)$$

$$u_{\sigma_t^s} = max\big(0, -m_{\sigma_t^s}\big) \ (3)$$

$$g_{\sigma_t^s} = max\big(0, m_{\sigma_t^s}\big) \ (4)$$

11

$$z_{\sigma_t^s} = min\left(y_t + g_{\sigma_t^s}, D_t^s + u_{\sigma_t^s}\right) (5)$$

$$I_{\sigma_t^s} = \pi \cdot z_{\sigma_t^s} - k_{prod} \cdot y_t - k_{inv} \cdot g_{\sigma_t^s} - k_{back} \cdot u_{\sigma_t^s} + I_{\sigma_{t-1}^{s-1}} (6)$$

$$b_{\sigma_T^s} = max\left(0, -I_{\sigma_T^s}\right) (7)$$

$$y_t, g_{\sigma_t^s}, u_{\sigma_t^s}, z_{\sigma_t^s} \geq 0 \ (8)$$

Following constrains are needed for each state (s) of each time period (t): material balance ($m_{\sigma_t^s}$), inventory level ($g_{\sigma_t^s}$), unmet demand ($u_{\sigma_t^s}$), units sold ($z_{\sigma_t^s}$) and balance in account ($I_{\sigma_t^s}$). Additionally, constraint for amount of borrowing at time T ($b_{\sigma_T^s}$) is needed. Following constants are defined for one unit: marginal cost of producing (k_{prod}), cost of carrying inventory (k_{inv}), backorder cost (k_{back}) and selling price (π). y_t is the supply requirement for each time period. D_t^s is the estimated demand for each state of each time period.

Material balance is obtained by the difference between supply and demand (2). If the demand is higher than the supply we obtain the unmet demand (3) with which we can calculate cost of not being able to deliver the product. Inventory level is the maximum of zero and material balance (4). If material balance is positive then we have spare products which increase the cost of inventory. Units sold equals to the minimum of the sum of supply and inventory level or the sum of demand and unmet demand (5). It is not possible to sell more than what is in the inventory. Finally the amount of cash is calculated by taking into account the cash generated in previous states, incomes from current sales and the cost of carrying inventory, of unmet demand and of production expenses (6). Also, we must calculate the borrowing level at time T which is the maximum of zero and minus inventory level at period T (7).

The objective function is the sum of weighted decision values (1), which are:

$$\lambda_1 \sum_{t=0}^{9} p_t \cdot u_{\sigma_t^T} \cdot k_{back} (9)$$

$$\lambda_2 \sum_{t=0}^{9} p_{T-t} \cdot g_{\sigma_{T-t}^T} \cdot k_{inv} (10)$$

$$\lambda_3 \sum_{t=0}^{9} \left(p_{T-t} \cdot b_{\sigma_{T-t}^T} + p_t \cdot b_{\sigma_t^T}\right) (11)$$

$$\lambda_{cBaR} + \lambda_{cIaR} + \lambda_{cDaR} = 1 \ (12)$$

The three different decision values are cDaR (9), cIaR (10) and cBaR (11), which are calculated as follows: probability of end state t (p_t) times cost of unmet demand, cost of inventory level or amount of borrowing at end state t. The weights are λ_1, λ_2 and λ_3 which satisfy equation (12).

These numerical values are calculated for following tail probabilities: cDaR includes the high demand states 0-9 (of 27 end states) which includes probability mass of 8,4%, cIaR considers low

demand states 17-26 which also sum up to 8,4%. For cBaR both high demand states 0-8 and low demand states 18-26 are included, yielding an aggregate probability of 7,6%.

Now we can solve problem (1) with excel solver by changing y_t which is the optimal supply quantity for period t.

4   Results of the model

First we will find an optimal solution for supply requirement by minimizing risk, then we shall try how the outcome is affected by changes in different variables and then we will compare the results between risk minimizing and profit maximizing.

The probabilities for different final states are plotted in Figure **Error! Reference source not ound.**7. As we can see from this figure the probabilities for tail states are very low. For every case we use same starting values for the selling price of the product, cost of production per unit, cost of carrying inventory and the backordering costs per unit. Although we will do some analysis how results will be affected by changes in these values. The forecast of demand is made based on initial demand which equals 1000 units per week and the most optimistic forecast is that the demand will grow for 1% each week and the most pessimistic is that it will decrease 0,25% per week.

Definition	Cost
Fixed production cost per product	2.5
Cost of carrying inventory per period	2
Loss caused by unmet demand per unit	2
Selling price of one product	3.5

Table 1 Used parameters

We conduct the analysis based on following assumptions: fixed production cost of a product is 2.5, cost of carrying inventory per item is 2 for one period and loss caused by unmet demand is 2 per unit. The selling price is based on the following assumptions: the company targets for 6% profit per product, we assume that the inventory level will be at 20% on average and 20% of demand will be delivered next week. With these assumptions we get a selling price of 3,5 for our product. We value the weight of each decision variable to be equivalent, in this case 0,33 for each. Probabilities for different demand scenarios are shown in Figure 6. As we can see from this figure it is highly unlikely to end up with a very high or very low demand.
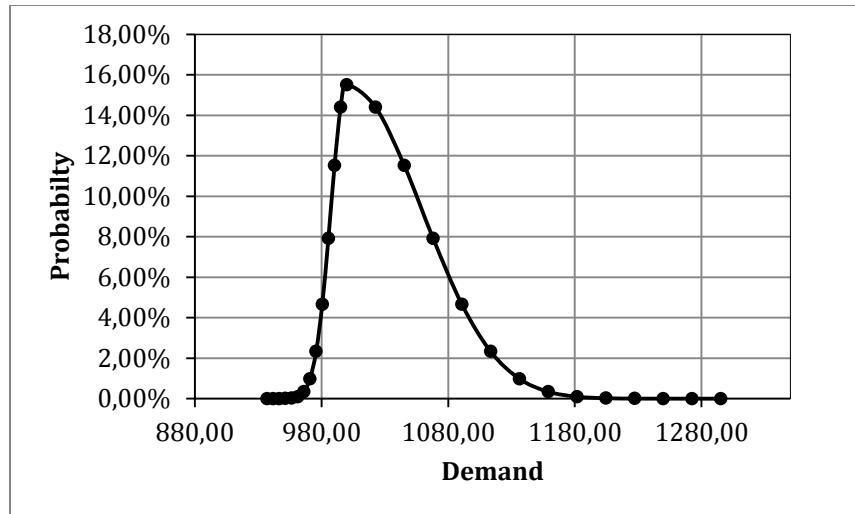
Figure 6 Probabilities for different demands

4.1   Minimizing risks

Results of minimizing risks by solving problem (1) are presented in the following section. Figure 7 shows the optimal supply requirement for each period. As can be observed from Figure 9, the supply is stable until state 10 and after that the supply increases until state 18. After state 18, the optimal solution drives inventory down by decreasing supply amounts significantly. The reason behind this is that based on our assumptions the planning season for this product is only 26 periods, so makes sense to reduce your inventory to the minimum at the end. This is why the model tries to get rid of the surplus inventory at all costs: even with the cost of possible backorders. It also makes sense because production cost for one unit is higher than the holding cost. This implies that it is more cost effective at some point to get rid of the surplus products by decreasing the quantity supplied.
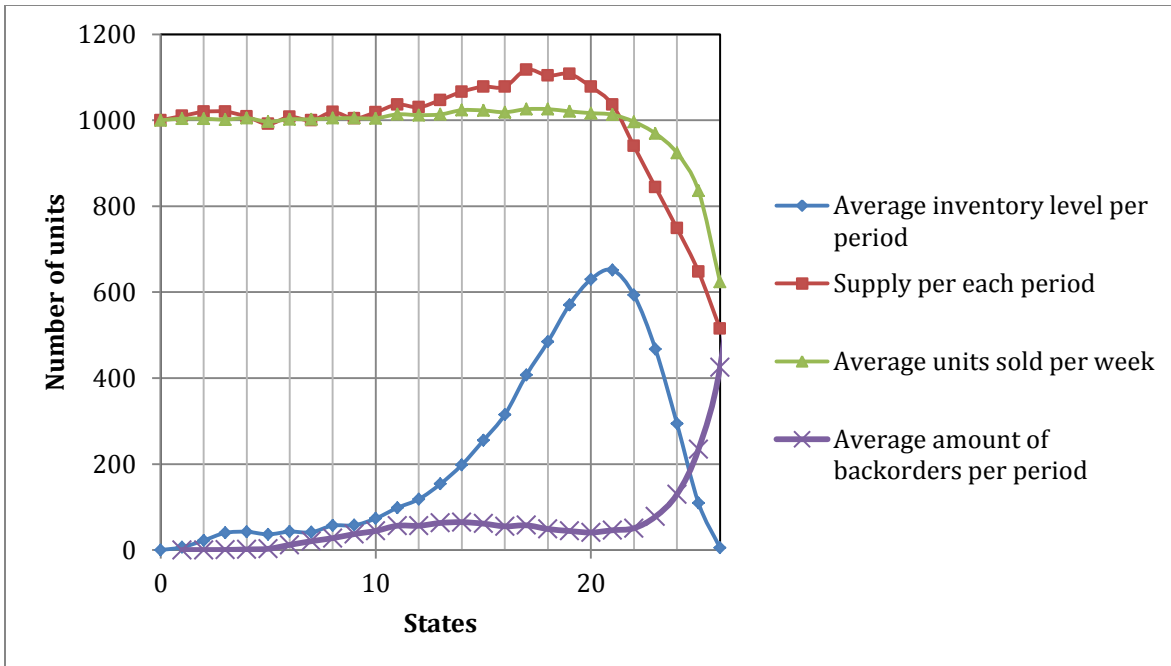
Figure 7 Relations between expected inventory level per period, supply per each period, expected units sold per week and expected amount of backorders per period, risk minimization.

As Figure 7 illustrates, the expected inventory per period increases for most of the time. This can be explained by inspecting the difference between supply requirement per each period and the expected units sold per each week. These figures confirm the intuition that it is better to have more products in the inventory than the actual demand is, just to make sure you can always meet the demand: especially in this case because the holding cost is the same as backorder cost.
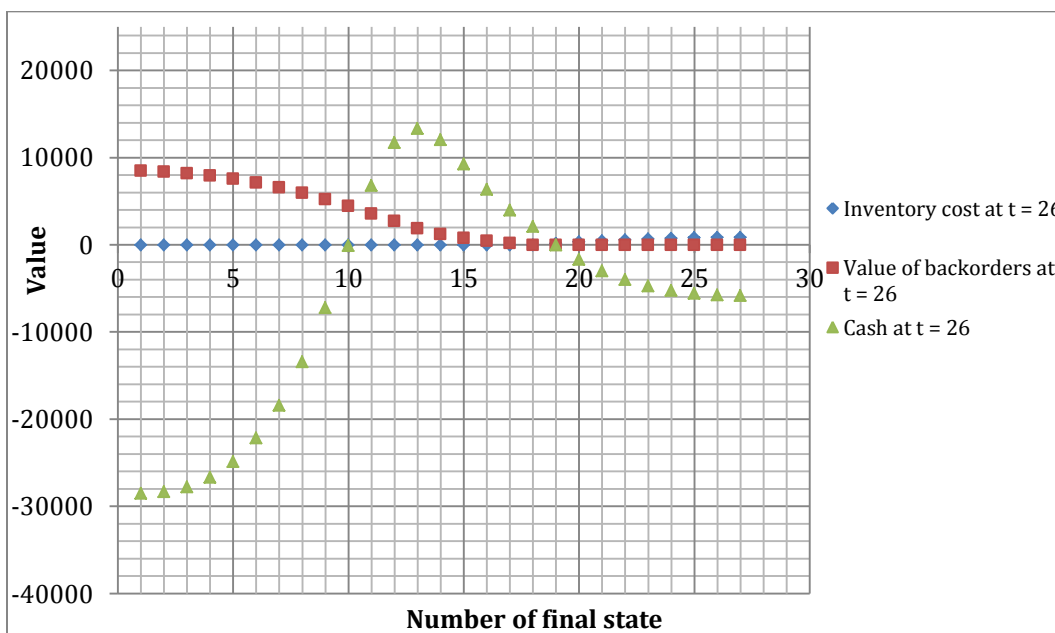

Figure 8 Values at t = 26.

Figure 10 shows the positive cash flows end up being between states 11 and 18 which are the most probable states. The probability for ending up into these states is over 82%. A company could make huge losses in the tail states, but the probabilities for those are relatively small. From the same figure it can be observed that whenever there are backorders in the end, the profits will be much more negative than only by having inventory. On the other hand, the inventory level does not have a large effect on the losses, compared to not being able to deliver the demanded products in time. The expected profit (with parameters of Table 1) is 7480 and the value of objective function (the weighted sum of decision variables) is 284.

If we change the cost of inventory to 1,5 and let other variables stay the same, the model becomes unstable: the fluctuations in results will be much bigger than in results where the cost of inventory is the same as the cost of backorders. In this case the expected profit is 10311 and weighted sum of risk measures is 181. Next we will see how same kind of change for cost of backorders will have in the results. In this case supply requirement becomes also a little more unstable and the expected profit will be 9879 and the risk is 141. The differences between these supplies can be seen in Figure 9.
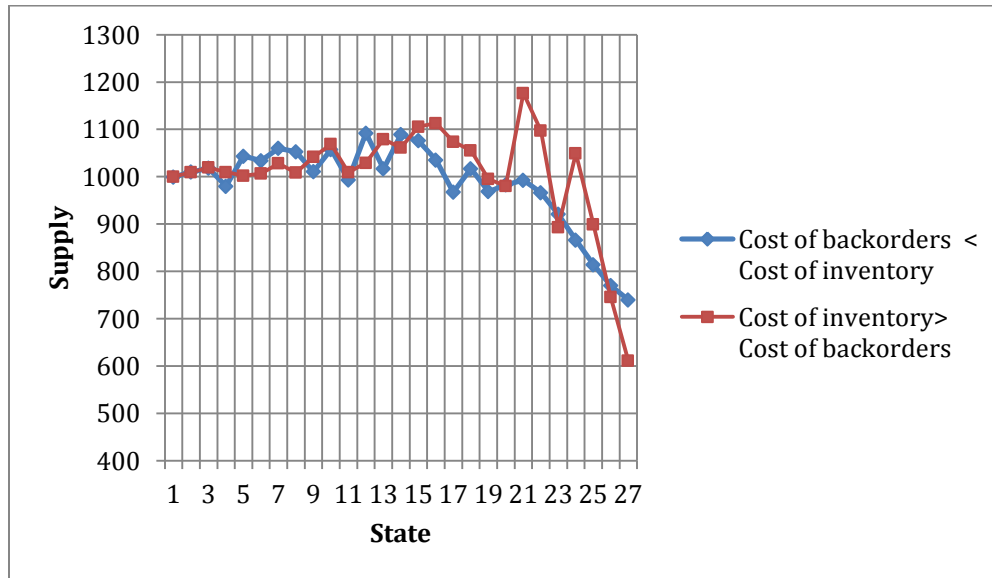

Figure 9 Supply requirement for different cost variables. Cost of inventory and backorders is changed, other variables are kept constant.

Next we analyze the importance of weights. Different weights are listed in Table 2. Comparing the original results to the weights (Figure 7 and Figure 10) it can be seen that the trend for required supply requirement is approximately the same for every case. The behavior of the model in Case 3 is somewhat surprising, but the reasons behind this behavior are left to subsequent studies.

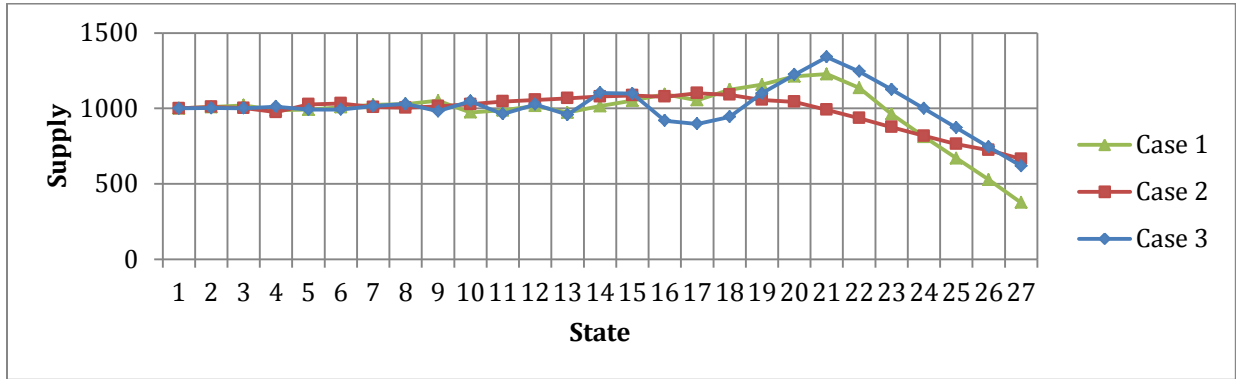|	CDaR	CIaR	CBaR
Case 1	0	0	1
Case 2	0,45	0,45	0,1
Case 3	0,3	0,1	0,6

Table 2 Different weights used for analysis

Figure 10 Supply for different weights, risk minimized
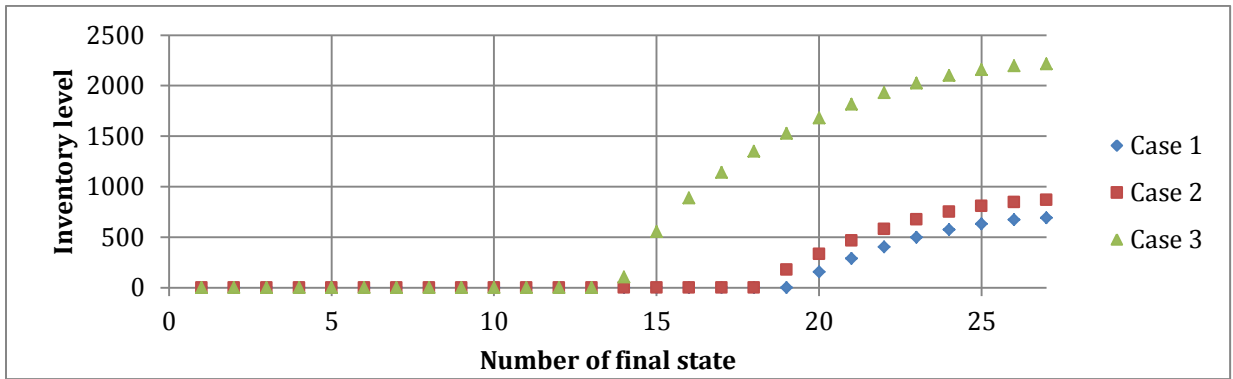

Figure 11 Inventory for different weights, risk minimized
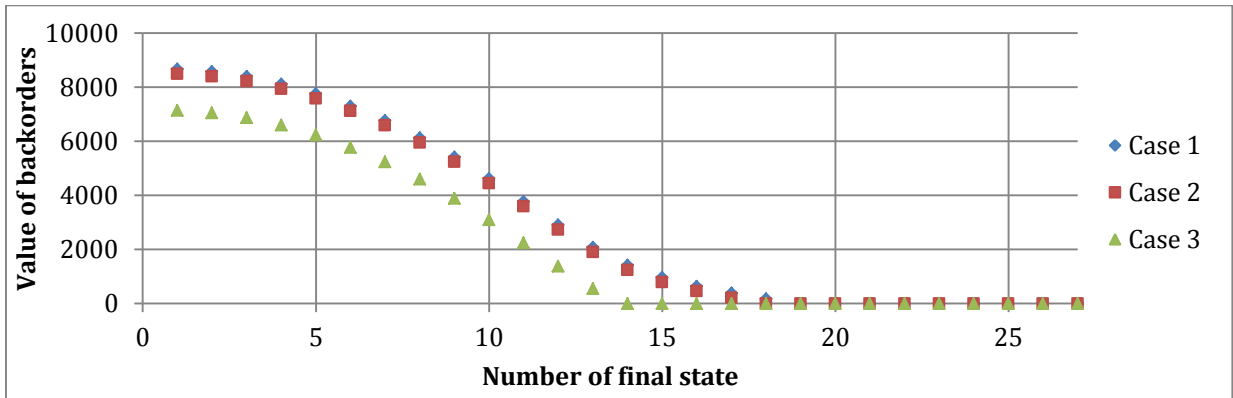

Figure 14 Value of backorders for different weights, risk minimized

As Figure 14 illustrates, for cases 1 and 2 the order value of backorders are almost the same, although the values at case 2 are a little lower all the time as they should be, because the weight for backorders is higher (0% vs. 35%). But what is interesting is that the case 3 is way below case 2 in value of backorders even it has lower weight of cDaR. However case 3 has a higher weight in amount of allowed borrowing. It seems that weight for debt has a bigger impact to the whole: it is wise to avoid losing sales because one get penalty for just losing the sales and secondly the

opportunity to gain profits by selling the actual product is missed. Thirdly, the value of inventory and backorders are included in the level of borrowing. Also a notification should be made that by analyzing the cost of inventory (Figure 11) we can see that for case 3 the inventory is much higher compared to others, even though it has the highest weight for inventory level.
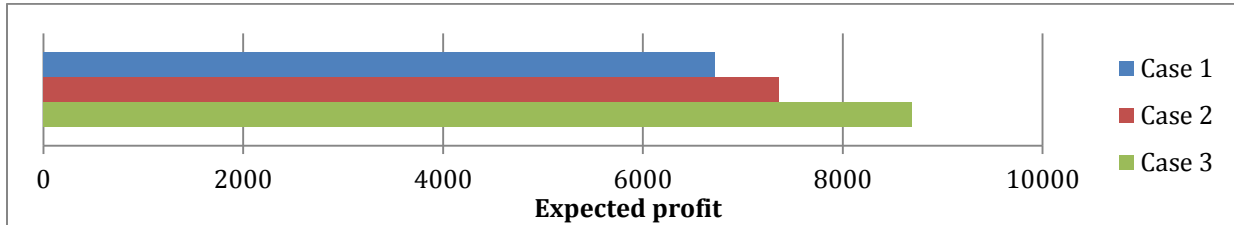

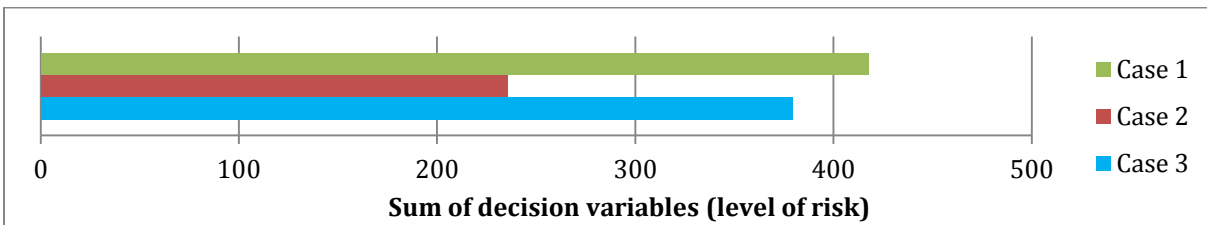*Figure 15 Expected profit for different weights, risk minimized*

Figure 16 Sums of decision variables, risk minimized

Based on Figure 15 case 3 would be the most profitable one but according to Figure 16 is the second most risky. What is interesting is that case 1 seems to provide the smallest profit but still it is the most risky one. Case two provides second best profit but it has significantly less risk than the others. Based on these figures we can see that, at least in certain cases, the more you give weight for borrowing at risk the riskier the overall result will be.

4.2 Maximizing profits

Figure 17 shows the results when the model maximizes expected profit instead of risk minimization. As Figure 17 shows, the model for finding an optimal solution for expected profit maximum is quite stable. At t = 24 supply requirement changes quite dramatically, which can not really be explained without further analysis of different variables.
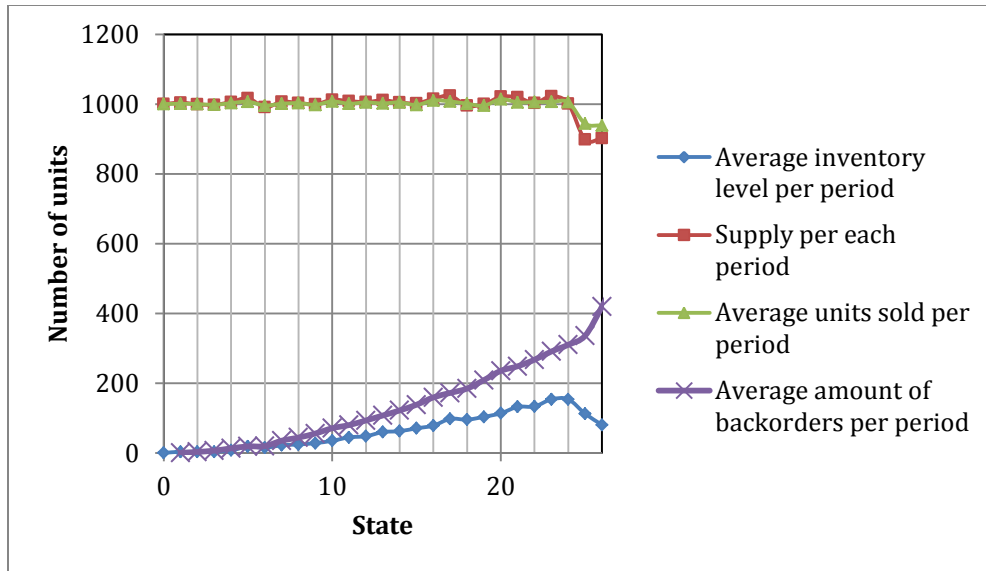
Figure 127 Relations between expected inventory level per period, supply per each period and expected amount of units sold per week, profit maximization.
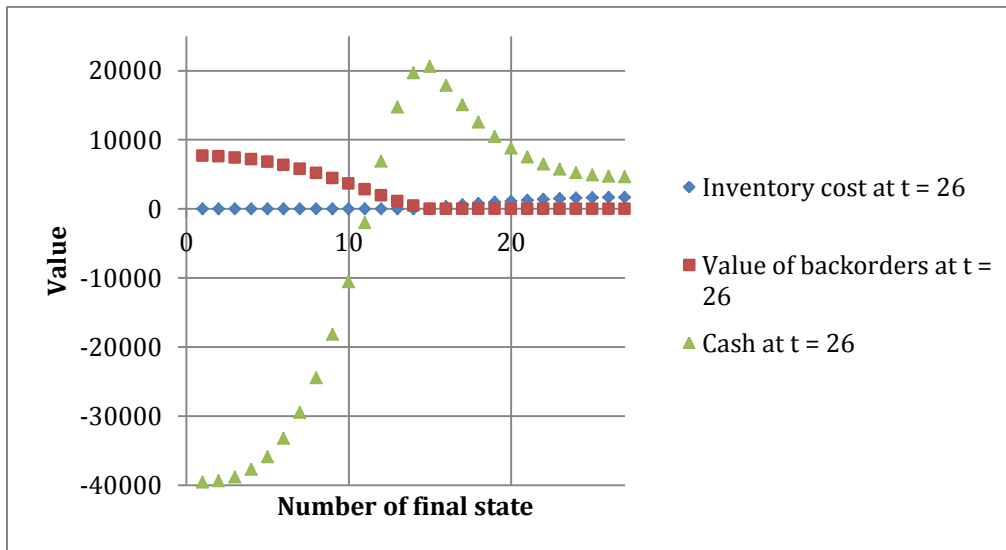

Figure 18 Values at t = 26

As Figure 18 shows the value of backorders has a big impact on the total profits: first of all you lose sales and then you have to bear the cost of inventory. This can change if the initial cost variables were different. For example, if the inventory cost is less (1,5) than cost of backorders (2,0) the expected amount of backorders at the last period decreases from around 420 to 292. If the situation was the other way around (cost of inventory 2,0 and cost of backorders 1,5) the results are approximately the same as with inventory cost being same as cost of backorders. Even the supply requirement is on average the same. On the other hand the expected profit of such setting (cost of inventory 2,0, cost of backorder 1,5) is 14548 while the expected profit for the other (cost of inventory 1,5 and cost of backorder 2,0) setting is only 12979 while expected profit for default

setting is 11669. With this information, we can conclude that it is possible to increase your profitability efficiently by lowering the costs of backorders. The cost for backorders is amplified in a way of lost sales, so this observation seems to be valid.

In default setting the chance of doing profit with maximizing profit -strategy is only 72% and the value for risk measurement is 411.

4.3   Discussion of the results

With risk minimizing supply requirement the chance of making profit is 82% while with profit maximization strategy the same probability is 72%. Expected profit with risk minimization is 7480 (the objective function value being 284) while the same figures for maximization approach are 11669 and 411. So, the risk minimization strategy gives as a better chance of gaining some profit but the expected profit is higher when profit is maximized.

As we saw previously, the supply requirement in the minimal risk scenario is quite low in the end because of the need to get inventory empty with the cost of unmet demand and therefore by losing sales. On the other hand in the end we will not have that much inventory, which, for some situations, is actually preferred. We must remember though that this is only what would happen on average based on our estimates. Although supply requirement was very stable for profit maximization, staying almost all the time around 1000, which was the actual initial demand forecast.

The risk minimization lowers the expected losses in tails of the value distributions. The idea is that if one ends up to a state with very high or low demand, the losses should not be extremely high: in this case minimizing risk is all about trying to make the profit distribution "more flat". In practice this means that the results would be good on average.

By maximizing profit the level of inventory does not have such a high priority to be minimized and also the level of backorders does not have that huge impact either. It seems that the most important difference between minimizing risk and maximizing profit is that in profit maximization, it is important to be able to deliver all products all the time.

In some cases the numerical results of the model were very unstable, meaning that first of all the supply requirement was for some reason fluctuating very much and in some cases the supply started to oscillate and increase tremendously. Excel might not be the best for solving such problems: in some cases the results differed a little even when the same initial values were used.

The objectives for risk minimizing are conditional-inventory-at-risk, conditional-borrowing-at-risk and conditional-demand-at-risk. Changing the weights of these variables decision maker can choose which section to have the most weight: inventory manager might prefer inventory-at-risk while borrowing-at-risk could be the best choice for a profit-orientated decision maker.

In optimization, it was assumed that it is equally probable for demand to go up or down. The results would most certainly differ if the probabilities were not equal. In such cases it should be considered if aggregation is still valid way of combining different scenarios. Further research should be made

to ensure this. What comes to the analysis of the used risk measurements, we could not come up with better ones: these variables takes into account all of the essential elements. Still, it might be worth considering if value of inventory and backorder costs could be separated from the level of borrowing to make the model more controllable. Also it would be interesting to see how an unexpected stepwise increase in demand would affect the outcome.

5 Conclusions

Based on our results, the presented model would suit best for approximating the supply requirement for a functional product which is produced in great amounts and the demand is quite stable. However, the model provided sometimes quite unstable supply requirement: results fluctuated without any clear explanation. Because of this instability and inability to take unexpected changes in demand into account, it seems that the Excel implementation is not suitable for products with highly varying demand. Or, this issue should be treated in greater extent in further research.

The analysis showed how changes in prices affect the expected profit of the whole production. Thus, the model could be used for finding which the most optimal way of reducing fixed costs is. By reducing fixed costs and uncertainty, companies are able to lower the selling price which once again increases their demand eventually leading to higher profits and volumes.

We found that the model is instable sometimes and in some cases it provided different results with the same starting values. This might be because of Excel's limited computational capabilities. On the other hand, Excel is very suitable tool to be used in S&OP type of process, because of the easiness of use. It is much easier to convince managers of a company with a forecast optimized plan made by commonly known software instead of a black box. Also, everybody can use Excel, which makes it easier to explain all details of the model thoroughly. This might be very important factor in when implementing models for a supply planning team. Furthermore, the technical implementation of the model is rather straightforward.

For further research we leave the analysis of another kind of objectives. The model's objectives include each other in a way: conditional-borrowing-at-risk includes the costs of excess inventory and costs of backorders and we still have different weights for the two. It could be investigated if other cost variables could be used. On the other hand these variables are good because they all must be valued in cash: this way these variables can be compared together. But it must be remembered that borrowing is amplified by the cost of inventory and cost of backorders so it has the biggest weight overall. In addition, it would be interesting to study how this model could be modified to use updated sales data to improve forecasts for next periods.

Different mathematical models are used for supply chain management and supply chain risk management to find the optimal way of managing operations. By S&OP companies can plan the operations of a company as a whole. The presented model can help companies to better prepare for uncertain demand, which is a key objective of SCRM. Some other ways to mitigate company's risks are a flexible supply network design, contracts, real options and right kind of management. Distributing the supply chain globally can help reducing local and international risks. Furthermore,

supply chain management should be seen as a holistic process: it is seldom optimal just to optimize own profits but by collaborating with partners productivity can be increased overall.

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7 Appendix

7.1 Summation of the Thesis in Finnish

Riskienhallinta on korostunut nykymaailman yritystoiminnassa. Yritykset pyrkivät vähentämään epävarmuutta käyttämällä erilaisia malleja toiminnan ennustamiseen ja suunnitteluun. Esimerkiksi kysynnän ennustaminen on havaittu hyväksi tavaksi vähentää kustannuksia ja saavuttaa parempia lopputuloksia yrityksen toiminnalle.

Riskien hallinta ja toiminnan mallintaminen ja ennustaminen on erityisen tärkeää toimitusketjujen hallinnassa ja siihen liittyvien riskien hallinnassa. Toimitusketjuun ja sen hallintaan kuuluu useita muuttuvia osa-alueita, joita ei voi täysin hallita. Erityisen tärkeää on käsitellä toimitusketjua kokonaisuutena eikä yksittäisinä osa-alueina. Tietyn osa-alueen optimointi huomioimatta muiden toimintaa johtaa tulokseen, joka ei vastaa globaalia optimia.

Tässä työssä käsitellään toimitusketjuja sekä niiden riskienhallintaa yleisellä tasolla. Työssä esitellään matemaattinen malli toimitusketjun tuotannon sekä riskien hallintaan. Lisäksi työssä vertaillaan mallin antamia tuloksia erilaisille tavoitetiloille: toisessa tilanteessa päätöksentekijä pyrkii minimoimaan riskit ja toisessa maksimoimaan voitot. Mallille tehdään myös herkkyysanalyysi.

Toimitusketjun hallinta on tuotteiden ja palveluiden koordinointia ja ohjaamista siten, että tuotteelle tai palvelulle tehtävät toimenpiteet luovat arvoa loppukäyttäjälle (Christopher 1998). Toimitusketju koostuu useista eri osakokonaisuuksista, minkä takia sen hallintaan kuuluu erilaisia riskitekijöitä. Toimitusketjut ovat yritysten yksi olennaisimmista aktiviteeteistä, minkä takia sen onnistunut hallinta voi antaa merkittäviä kilpailuetuja. Alalla hyvin tunnettu ilmiö nimeltä "Bullwhip effect" on hyvä esimerkki siitä, kuinka kommunikointi ja tiedon pihtaus voi johtaa valtaviin kysynnän ennustamisen epäonnistumisiin (Lee et al. 1997). Kyseinen ilmiö kuvaa sitä, kuinka pieni muutos toimitusketjun loppupäässä (lähellä kuluttajaa) voi aiheuttaa valtavan kysynnän virhearvioinnin toimitusketjun alkupäähän (valmistaja) puhtaasti puutteellisen tiedonkulun takia.

Yksinkertaistettuna on olemassa kahdenlaisia tuotteita: funktionaalisia ja innovatiivisia tuotteita (Lee 2002). Funktionaalisten tuotteiden kysyntä on stabiilia ja elinkaaret pitkiä. Innovatiiviset tuotteet taas omaavat lyhyemmän elinkaaren ja ne ovat yleensä korkean teknologian tuotteita. Tällaisten tuotteiden kysyntää on yleensä vaikea ennustaa. Innovatiivisten tuotteiden ennustamista vaikeuttaa myös se, että yleensä niiden kysynnästä on todella vähän tai ei ollenkaan historiatietoja käytettävissä.

Tang:n (2006) mukaan toimitusketjujen riskienhallinta on toimitusketjun hallintaa siten, että voitollisuus ja jatkuvuus pystytään takaamaan. Tässä työssä tähän asiaan perehdytään tarkemmin mallintamisen yhteydessä vertailemalla riskien minimointia ja voiton maksimoinnin antamia mallintamistuloksia.

Toimitusketjun riskienhallintaan kuuluu neljä kokonaisuutta: tuotannon hallinta, kysynnän hallinta, tuotteen hallinta sekä informaation hallinta. Tärkeimmiksi riskienhallintamenetelmiksi nousevat miten ja miltä alueilta valita sopivat kumppanit, onnistuneet toimittajasopimukset, kysynnän hallinta eri hinnoittelu menetelmillä, onnistunut kysynnän ennustaminen eri menetelmin, alustojen käyttäminen monimutkaisissa tuotteissa sekä informaation vaihtaminen toimijoiden välillä.

Myynnin ja operaatioiden suunnittelu –prosessi on keskeisessä roolissa yritysten kokonaisuuden hallinnassa. Kyseinen prosessi yhdistää myynnin, markkinoinnin, tuotannon ja talouspuolen. Ottamalla huomioon kaikkien toimijoiden intressit kokonaisuudessa pystytään yrityksen toimintaa optimoimaan paremmin.

Kysynnän ennustaminen voi olla hankalaa tai jopa mahdotonta joissain tilanteissa. Riskienhallinnasas ja ennustamisessa tärkeätä on se, että lasketaan ennusteisiin riski mukaan siten, että lopullinen suunnitelma sietää muuttuvia olosuhteita ja riskitekijöitä paremmin. Tätä varten on järkevä käyttää esimerkiksi odotusarvoja laskennassa, koska tällä tavoin voidaan arvioida mitä tapahtuu keskimäärin ja yleensä se on riittävä arvio tulevasta. Toisaalta päätöksentekijän pitää ottaa muut vaikuttavat tekijät, esimerkiksi kysyntäskenaariot, huomioon päätöstä tehdessä. Kysyntä/tarjonta skenaariot voidaan ajatella jakaumana ja minimoidakseen riskiä voidaan minimioida jakauman häntäpäissä tapahtuvia menetyksiä. Yleensä juurikin nämä jakauman häntäpäiden tilat ovat niitä, jolloin saavutetaan suurimmat tappiot, joten tappioiden minimointi näissä tilanteissa vähentää kokonaisriskiä merkittävästi.

Stokastinen optimointi soveltuu toimitusketjujen käsittelyyn, koska stokastisilla malleilla pystytään ottamaan huomioon toimitusketjujen epävarma luonne huomioon (Birge et al. 1997). Stokastisessa optimoinnissa voidaan tietyllä tavalla tehdä päätöksiä dynaamisesta eri tilojen välillä. Tämä mahdollistaa sen, että stokastisessa optimoinnissa voidaan ottaa huomioon eri tilojen välillä tapahtuvat satunnaiset tapahtumat. Lisäksi tällaisessa mallintamisessa huomioidaan koko ajanjakso mitä optimoidaan, ei ainoastaan yksittäisten tilojen tilaa. Tärkeimmät sovelluskohteet stokastiselle optimoinnille ovat toimitusketjujen mallintamisessa, finanssialalla, energia-alalla sekä transportaatio teollisuudessa (Morton 2004). Stokastisessa optimoinnissa lähtökohtana on se, että epävarmojen muuttujien jakaumat tunnetaan tai ne pystytään vähintäänkin estimoimaan.

Stokastisessa optimoinnissa on periaatteessa kahden tyyppisiä tilanteita: kahden tilan sekä useamman tilan tehtävät. Kahden vaiheen tehtävissä on ainoastaan alkutila ja lopputila, joiden välissä tapahtuu jokin satunnainen tapahtuma, joka vaikuttaa lopputilaan. Useamman tilan tehtävässä on kuten kahden tilan ongelma, mutta alkutilan ja lopputilan välillä on useita välitiloja ja jokaisen tilasiirtymän välillä voi tapahtua satunnainen muutos, joka vaikuttaa seuraavaan tilaan. Stokastisessa optimoinnissa optimointi tehdään dynaamisesti jokaisen tilan välillä, joka tarkoittaa tässä sitä, että satunnainen tapahtuma otetaan päätöksessä aina huomioon.

Jos jokaisella tilalla on eri todennäköisyys, niin ongelma on polkusidonnainen. Tämä tarkoittaa sitä, että jokainen yksittäinen tila ei kuvaa koko systeemiä täysin, koska aiemmilla askeleilla on myös vaikutusta nykyiseen tilaan. Tällaisissa tapauksissa käytetään skenaarioiden aggregointi – menetelmiä, jolloin jokaisen tilan arvo aggregoidaan aiempien tilojen perusteella.

Stokastisessa optimoinnissa voidaan käyddää useita päätösmuuttujia ja lähtökohtia alkuperäisen ongelman ratkaisemiseen. Usein lähtökohtana on voittojen maksimointi, mutta tästä voi aiheutua suuria riskejä. Lähtökohtana voidaan käyttää myös riskien minimointia, joka on yleensä kannattavempaa ajatellen toimintaa pitkällä aikajaksolla. Tällä tavoin yrityksen toiminta on pitkällä aikajaksolla stabiilimpaa ja ennustettavampaa. Lisäksi tällaisessa ennustamisessa voidaan käyttää erilaisia päätösmuuttujia, esimerkiksi huomioimalla resurssit.

Value-At-Risk mittaa käytetään usein riskimittarina finanssialalla portfolioiden hallinnassa, mutta sitä voidaan soveltaa myös muualle. VaR on se arvo, mikä tulee toteutumaan tietyllä todennäköisyydellä. Riskitasoa voidaan säätää vaikuttamalla todenäköisyysjakauman häntäjakauman muotoon. Toisinsanoen tämä tarkoittaa sitä, että pyritään vaikuttamaan todennäköisyyteen ja riskin suuruuteen. Tämän työn kannalta olennaisempi riskimittari on odotusarvoinen Value-At-Risk, joka on odotusarvo mentettävän arvon suuruudesta häntäjakaumassa.

Stokastisen optimoinnin työkaluja voi hyvin soveltaa myynnin- ja operaatioiden suunnittelu – prosessissa. Tässä työssä esitellään malli, joka soveltaa näitä menetelmiä (Sodhi 2010). Mallintamisen lähtökohta on se, että päätöksentekijä tietää tuotteensa tuotantokustannukset, varastointikustannukset, myöhässä toimitetun tavaran kustannukset, tuotteen myyntihinnan, suunnitteluajanjakson pituuden sekä kysyntäskenaariot eri ajanhetkille. Mallia käytetään optimaalisen tuotantokapasiteetin määrittämiseen eri ajanhetkillä. Sodhin mallin tärkein sovelluskohde on se, että sillä pystytään minimoimaan riskejä ts. minimoimaan tappioita jakauman häntäpäissä eli harvinaisissa tilanteissa. Malli implementoidaan Microsoft Excelillä. Excelissä käytetään apuna Excelin omaa "Solver" –työkalua. Perimmäinen ajatus mallissa on se, että minimoidaan ehdollisia VaR –arvoja kolmen eri muuttujan suhteen: odotusarvoinen lainan määrä, odotusarvoinen varaston määrä sekä odotusarvoinen kysyntä.

Ajanjakson rajoitettu pituus johtaa siihen, että riskejä minimoimalla jossain vaiheessa tuotanto kannattaa laskea alle kysynnän, että varasto saadaan tyhjäksi ajanjakson päätyttyä. Tällainen tulos antaa vaikutteita siitä, että mallia voisi soveltaa reaalimaailman ongelmiin. Toisaalta myös kustannusmuuttjien valinnalla on vaikutusta siihen, miten tuotantokäyrä lopulta käyttäytyy ajanjakson loppupäässä. Riskien minimoinnin tapauksessa päädyttiin tulokseen, jossa todennäköisyys päätyä voitolle oli 82%. Tuottojen maksimoinnissa sama todennäköisyys oli vain 72%, mutta odotettu tuotto oli merkittävästi suurempi: voiton maksimointi antoi arvon 11669, kun taas riskien minimointi antoi tulokseksi vain 7480.

Tulosten perusteella malli näyttää toimivan järkevästi ja sitä voisi soveltaa reaalimaailman ongelmiin tietyin rajoittein. Riskejä minimoimalla pystyttiin minimoimaan menetyksiä häntätodennäköisyyksissä, mikä antoi keskimäärin useammin voitollisen tuloksen. Voiton maksimointi –tilanteessa päädyttiin useammin tappiolle, mutta voitot suurenivat tietyillä todennäköisyyksillä. Mallin tärkeimmäksi hyväksi puoleksi tunnistettiin se, että se on melko helposti implementoitavissa yleisesti tunnetulla välineellä, eli tässä tapauksessa Microsoft Excelillä. Mallin tulokset on myös helpommin perusteltavissa päättäjille, koska todennäköisesti näillä päättäjillä on tietämystä kyseisestä ohjelmistosta ja täten voivat saada mallintamisesta paremman ymmärryksen. Ongelmallista oli se, että tietyllä tavalla odotusarvoinen velkaantuminen

huomioidaan jo odotusarvoisen varaston sekä odotusarvoisen kysynnän kustannuksissa, jolloin velkaantumisen painokerroin saattaa vääristyä. Jatkokehityskohteena voisi kehittää tätä osa-aluetta.